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DEVELOPMENT OF A SURFACE DISTRESS INDEX PREDICTION FRAMEWORK USING ARTIFICIAL NEURAL NETWORKS FOR ROADS INFRASTRUCTURE MANAGEMENT

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ABSTRACT

Road infrastructure is a crucial element of urban development, affecting transportation efficiency and road safety. Conventional techniques for evaluating road conditions often fail to capture the full complexity of deterioration and damage over time. This study explores the potential of Artificial Neural Networks (ANN) in predicting road conditions to optimize sustainable infrastructure management. The model was trained using a dataset comprising 2.467 observations of road damage collected over five years from 42 urban road sections. By integrating surface damage parameters such as crack area, crack gap, pothole, and rutting, the model was configured with 4 neurons in the first hidden layer and 4 neurons in the second hidden layer. The predictive model for the Surface Distress Index (SDI) revealed excellent performance, achieving an R^2 value of 0.95, a Mean Absolute Error (MAE) of 0.02, and a Root Mean Square Error (RMSE) of 0.05. The model can be effectively applied to assess road conditions with a high level of precision and reliability.

Keywords: ANN; predictive modeling; road conditions; road maintenance; SDI

INTRODUCTION

Road infrastructure is essential for developing mobility and enhancing urban connectivity. Road conditions influence investments in maintenance and road safety, which have a positive impact on economic growth (Ibrahimov et al., 2023; Kehagia & Giannaki, 2022; Keoudone & Xu, 2024; Nairobi & Respitasari, 2021). This issue highlights the urgency of advancing research on infrastructure management to sustain sustainable road infrastructure and improve urban mobility. The impact of road infrastructure on urban mobility is a regional phenomenon that necessitates solutions customized to each region (Dilrukshi & Jayasinghe, 2023; Kalaoane et al., 2024; Khanani et al., 2021; Olorunfemi et al., 2022). Infrastructure improvements must align with regional needs and be technologically integrated to address urban mobility challenges (Bono et al., 2023; Guo & Guo, 2023; Kussl & Wald, 2022; Sulistyo et al., 2024; Zinno et al., 2023). Well-developed road infrastructure provides significant benefits for transportation, serving as one of the primary drivers of sustainable economic growth (Z. Chen & Li, 2021; Sihombing & Aritonang, 2024; Thuy, 2019).

Emphasizing the importance of road maintenance, the transition in infrastructure condition assessment is crucial for achieving sustainability goals through stakeholder collaboration and the development of adaptive knowledge renewal in road condition evaluation (Chamorro et al., 2020; Koks et al., 2019; Larsson & Larsson, 2020; Wanume et al., 2023; Xue et al., 2021). Recent advancements in predictive modeling for road condition assessment have become a preferred approach, considering infrastructure, safety, and environmental aspects (Arshad et al., 2021; Luo et al., 2021). At present, the trend in road condition assessment is toward models that are based on machine learning, such as Artificial Neural Networks (ANN) ,a technology classified under Artificial Intelligence (AI), to predict Pavement Condition Index (PCI) values with high reliability and accuracy (Issa et al., 2022; Mahmood et al., 2023; Sirhan et al., 2022) as well as models for predicting the International Roughness Index (IRI) (Abdelaziz et al., 2020; Abdualaziz Ali et al., 2023; Bashar & Torres-Machi, 2021; Duckworth et al., 2022). Similar studies have integrated Artificial Neural Networks (ANN) into predictive models, resulting in improved prediction accuracy (Alharbi & Smadi, 2019; Mahmood & Khaleel, 2022).

The primary goal of this study is to create a predictive assessment model for the Surface Distress Index (SDI) in urban roads. This model will be based on Artificial Neural Networks (ANN) and will incorporate surface distress parameters, including crack area, crack gap width, pothole , and rutting. This research aims to enhance road maintenance strategies through a more adaptive, efficient, and comprehensive planning approach to promote a safer and more sustainable transportation system.

METHOD

This investigation aims to develop a predictive assessment model for road conditions by using the Surface Distress Index approach along with Artificial Neural Networks, which will facilitate data-driven decision-making in road maintenance. The model was trained using a dataset comprising 2,400 road damage observations collected from 42 urban road segments over five years. The variables were selected based on key indicators for assessing road surface conditions, including crack length (X1), crack width (X2), crack gap (X3), pothole (X4), rutting (X5), and SDI as the dependent variable (Y). The predictive model was developed using Machine Learning (ML) techniques implemented in R Studio software.

The dataset was divided into three categories for modeling: 60% training data (1,481 observations), 20% testing data (494 observations), and 20% validation data (492 observations) to ensure model stability and accuracy. The training procedure attempts to understand the correlation between research variables, while data measurement is used to assess the model's success in predicting road conditions not present in the training data. Validation occurs during the training process to prevent model overfitting and to ensure effective generalization to unseen data. The Artificial Neural Network framework is illustrated in Figure 1.

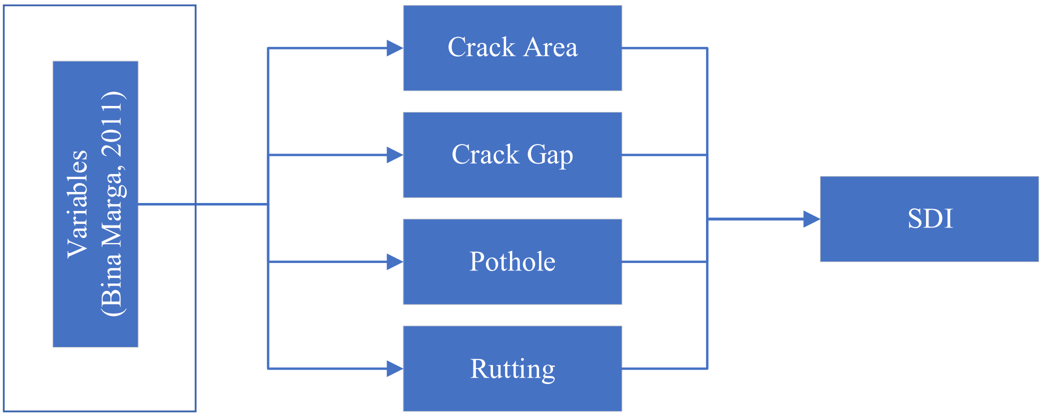

Figure 1. Framework for Artificial Neural Network Adoption

The validation metrics used to assess the model's performance include the Coefficient of Determination (R^2), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). R^2 assesses the model's capacity to elucidate data variability, whereas MSE and RMSE evaluate the disparity between anticipated and actual values. These metrics assess the model's accuracy in forecasting the Surface Distress Index and its dependability in identifying road segment deterioration for data-driven decision-making in road maintenance.

RESULT AND DISCUSSION

In data analysis, the exploration between input variables as predictors and output variables representing road condition values is achieved through correlation analysis. Figure 2 below presents a correlation five independent variables (X1 to X5) and one dependent variable (Y). The correlogram is a graphical representation that illustrates the relationships between variables in a dataset, including Pearson correlation (Corr), scatter plots, and distribution graphs.

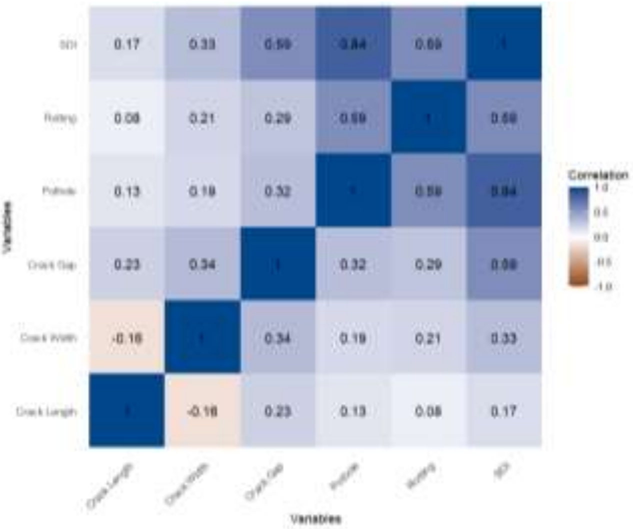

Figure 2. Correlogram of the SDI Prediction Model

The primary relationship between Y and the independent variables exhibits varying correlation strengths. Variable X4 has the highest correlation with Y, at 0.84, which is highly significant, indicating a strong relationship between the two. Meanwhile, X3 and X5 have moderate correlations with Y, at 0.59 and 0.59, respectively, suggesting weaker but still significant relationships.

The model configuration selection process tested several model configurations by evaluating their prediction performance using the R² value as the main indicator. From the 20 configurations with the highest R² values, the top five were selected for further analysis. The selection is done carefully to create a model that perfectly fits the training data, produces accurate predictions on the validation data, and thus optimizes to avoid overfitting. The ANN structure results from 20 configurations based on the R² value on the validation data can be seen in Table 1.

The outcomes of each training hidden layer configuration indicate that the artificial neural network model can effectively predict the validation data. Based on the R² value, the top five configurations were selected: Configuration 19 (R² = 0.9023186, 4-3 neurons), Configuration 16 (R² = 0.8942895, 3-4 neurons), Configuration 17 (R² = 0.8866008, 4-1 neuron), Configuration 20 (R² = 0.8842385, 4-4 neurons), and Configuration 14 (R² = 0.8828958, 3-2 neurons). Configuration 19 with a 4-3 neuron architecture achieved the best performance with MAE = 0.0377280 and RMSE = 0.0683176, indicating adequate learning ability in complex data patterns.

Table 1.
Results of Artificial Neural Network Structure Validation

Configurations	Hidden Layers	Neuron Structure	Dataset	MAE	RMSE	R^2
Config 1	1	1	Validate	0.0616123	0.0935695	0.8167618
Config 2	1	2	Validate	0.0495659	0.0849946	0.8488076
Config 3	1	3	Validate	0.0513083	0.0860939	0.8448713
Config 4	1	4	Validate	0.0495922	0.0832052	0.8551066
Config 5	2	1-1	Validate	0.062022	0.0937724	0.8159661
Config 6	2	1-2	Validate	0.0514518	0.0875818	0.8394630
Config 7	2	1-3	Validate	0.0619429	0.0937242	0.8161553
Config 8	2	1-4	Validate	0.0619041	0.0936957	0.8162673
Config 9	2	2-1	Validate	0.0532238	0.0864808	0.8434738
Config 10	2	2-2	Validate	0.052781	0.0862524	0.8442996
Config 11	2	2-3	Validate	0.0485954	0.0885214	0.8360000
Config 12	2	2-4	Validate	0.0486676	0.0844066	0.8508922
Config 13	2	3-1	Validate	0.0396232	0.0825154	0.8574993
Config 14	2	3-2	Validate	0.0407053	0.0748019	0.8828958
Config 15	2	3-3	Validate	0.0384851	0.0794747	0.8678081
Config 16	2	3-4	Validate	0.0337167	0.0710698	0.8942895
Config 17	2	4-1	Validate	0.0368154	0.0736091	0.8866008
Config 18	2	4-2	Validate	0.0389452	0.0795890	0.8674275
Config 19	2	4-3	Validate	00.037728	0.0683176	0.9023186
Config 20	2	4-4	Validate	0.0374069	0.0743718	0.8842385

After that, Config 16 was observed, and its slightly lower performance ($R^2 = 0.8942895$) should be mentioned because it also provided excellent MAE = 0.0337167 and RMSE = 0.0710698. It can be interpreted from this trend that different, balanced, and relatively simple neuron structures (4-3, 4-4) result in higher accuracy. Overall, these results confirm that 2 hidden layers consistently outperform 1 hidden layer, with the increased complexity in the neuron structure allowing the model to capture non-linear relationships in the road damage data more effectively.

The model evaluation was performed by calculating three main metrics, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination R^2, on the training, validation, testing, and all data. MAE is used to measure the average absolute error between the actual and predicted values, without considering the direction of the error, providing a direct interpretation of the average deviation in the same units as the data. Conversely, RMSE places more weight on larger errors because it first involves squaring them, making it more sensitive to outliers. R^2, the coefficient of determination, indicates how well the model explains the variability of the target data, with values ranging from 0 to 1, where a value closer to 1 indicates excellent predictive ability.

The evaluation is conducted in three steps, the main one being on the training data to see how effectively the model has learned from the historical data. The validation data, the validation dataset to see how accurately the model generalizes to unseen data provided during training, and the test data to see how successfully the model performs on data it has seen in actual scenarios. By analyzing each of these datasets and observing the combinations between alternative choices, a clear representation of what happens when evaluating model performance will be obtained. These metrics are used to evaluate the accuracy of the model's predictions and its ability to generalize to new data. The results of these metrics are presented in Table 2.

Table 2.
Metric Evaluation on Training, Validation, Testing, and All Data

Neuron Structure	Data	MAE	RMSE	R^2
4-3	Train	0.03947	0.07288	0.89819
	Validate	0.03998	0.07800	0.87266
	Test	0.03778	0.07007	0.89561
	All	0.03923	0.07339	0.89288
3-4	Train	0.04293	0.07758	0.88463
	Validate	0.04484	0.08348	0.85415
	Test	0.04301	0.07673	0.87484
	All	0.04333	0.07863	0.87704
4-1	Train	0.04239	0.08037	0.87620
	Validate	0.04149	0.07757	0.87407
	Test	0.03803	0.06835	0.90068
	All	0.04134	0.07755	0.88039
4-4	Train	0.03818	0.06651	0.91521
	Validate	0.03813	0.06803	0.90313
	Test	0.03760	0.06139	0.91988
	All	0.03805	0.06583	0.91381
3-2	Train	0.03726	0.06743	0.91284
	Validate	0.03880	0.07829	0.87171
	Test	0.03949	0.07552	0.87875
	All	0.03801	0.07138	0.89868

The most optimal predictive model consists of two hidden layers with a 4-4 neuron configuration in the artificial neural network. The first layer contains four neurons, and the second layer also contains four neurons. This model structure receives five input variables representing road damage conditions obtained from field observations, including crack length, crack width, crack gap, pothole, and rutting, which are implemented as the input layer in the artificial neural network. Figure 3 illustrates the predictive model for the Surface Distress Index using an Artificial Neural Network.

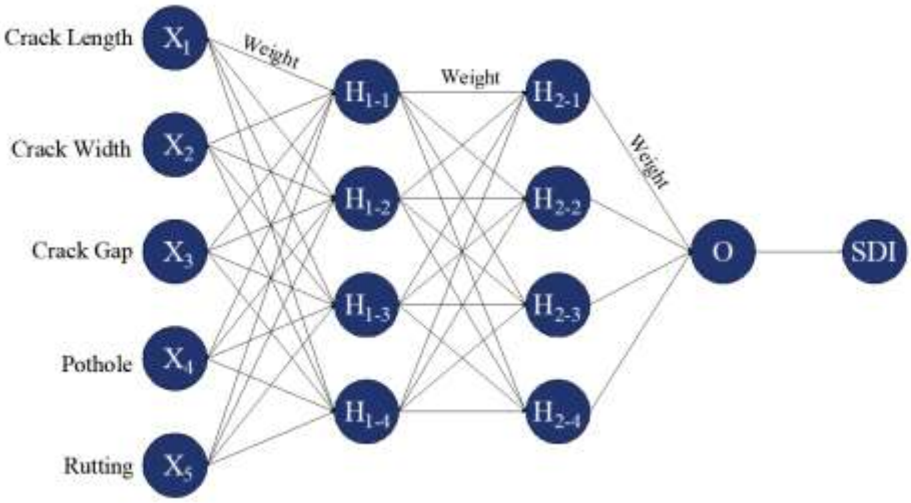

Figure 3. Architecture of the SDI Artificial Neural Network Model

In this model, the first layer consists of input variables, including crack length (X1), crack width (X2), crack gap (X3), pothole (X4), and rutting (X5). With two hidden layers configured in a 4-4 neuron structure, the Artificial Neural Networks predictive model for the Surface Distress Index can be interpreted as follows:

$$\text{SDI}= \sigma\left(\sum_{k=1}^{4} u_k \cdot \sigma\left(\sum_{j=1}^{4} w_{kj} \cdot \sigma\left(\sum_{i=1}^{5} v_{ji} \cdot x_i + b_j\right) + ck\right) + d\right) + \epsilon$$

Uk describes the weight value of the connection between the neurons in the second hidden layer and the output layer. Wkj describes the weight value of the link between the first hidden layer and the neurons in the second hidden layer. Vji describes the weight value of the connections among the neurons in the first hidden layer. bj, ck, and d describe the bias values in the neurons of each layer. σ describes the sigmoid activation function, while ϵ signifies the error.

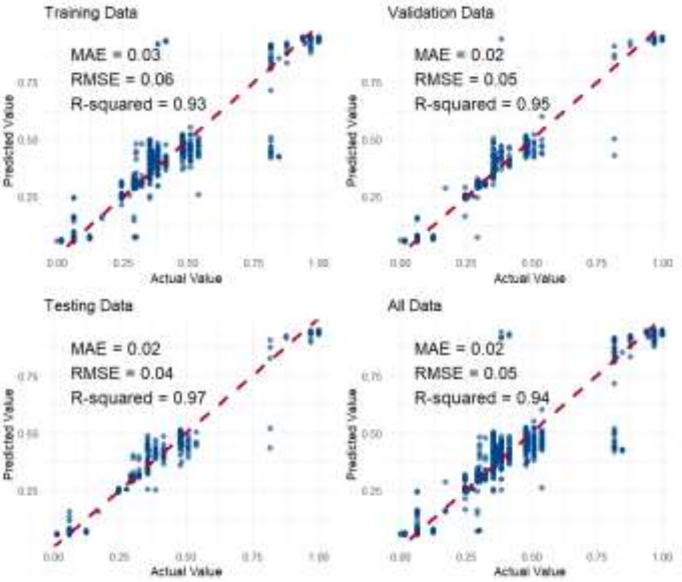

Figure 4. Performance of the Artificial Neural Networks Model

This model has excellent capability in generalizing unseen data during training, as indicated by an R-squared value of 0.95 on the validation data. The R-squared values across different data subsets consistently range from 0.93 to 0.97, confirming that no overfitting occurs in this model and that it remains valid within the context of data-driven prediction. The results confirm that the Artificial Neural Network model developed has strong predictive performance and can be effectively applied for road condition assessment in planning road maintenance activities with a high level of precision and reliability. The performance metrics in Figure 4 indicate that the model successfully explains most of the variability in the target data, and the prediction accuracy is reflected in the MSE and RMSE values.

The Surface Distress Index predictive model demonstrates exceptional generalization abilities for unseen data during training, evidenced by an R-squared value of 0.95 on the validation dataset. In the validation phase, the model's performance was assessed using Mean Absolute Error (MAE), giving a value of 0.02, signifying a small average deviation of predictions from actual values, hence demonstrating the model's high accuracy and precision. The Root Mean Square Error (RMSE) resulted in a value of 0.05, signifying a low average prediction error. This Artificial Neural Network predictive model exhibits competitive prediction accuracy, comparable to current PCI and IRI prediction models, which possess R^2 values between 0.93 and 0.99 (Abaza, 2023; Kheirati & Golroo, 2022; Rifai, 2023; Sharma et al., 2023; Sirhan et al., 2022; Wang et al., 2021).

These findings further validate that Artificial Neural Networks proficiently represent non-linear and intricate interactions among numerous input variables with more accuracy than linear regression models (K. Chen et al., 2025; L. Chen et al., 2024; Kwon et al., 2024; Oktopianto et al., 2025). The results obtained confirm that the developed Artificial Neural Network (ANN) model has strong predictive performance and can be applied for road condition assessment in road maintenance planning activities with an excellent level of precision and reliability.

CONCLUSION

The Surface Distress Index predictive model developed using an Artificial Neural Network consists of two hidden layers with a configuration of 4 neurons in the first hidden layer and 4 neurons in the second hidden layer. The Artificial Neural Network predictive model with a 4-4 neuron configuration demonstrates excellent predictive capability and precision in generalizing data, achieving an R-squared value of 0.95. The Mean Absolute Error (MAE) of 0.02 indicates that the average deviation of predictions from actual values is minimal, reflecting high model accuracy and precision, while the Root Mean Square Error (RMSE) of 0.05 signifies that the average prediction error is very low. This model can serve as a primary alternative for assessing road conditions with high precision and reliability, supporting road maintenance strategies through a more adaptive and comprehensive planning approach to promote a safer and more sustainable transportation system. The use of various diverse datasets can be expanded in future research to create better coverage in the predictive model of road surface deterioration, such as traffic volume, heavy vehicle count, and weather data as part of the dataset to predict the Surface Distress Index.

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